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Exploring Individual Differences in Task Switching

Bingxin Li^{1*}, Xiangqian Li¹³, Gijsbert Stoet², Martin Lages¹,

¹School of Psychology, University of Glasgow, Glasgow, UK

²Department of Psychology, University of Essex, Colchester, UK

³School of Social Development and Public Policy, Fudan University, Shanghai, China

Corresponding author:

Bingxin Li

School of Psychology

University of Glasgow

Glasgow G12 8QB, UK

Telephone: +44 (0)1413306165

E-mail: b.li.3@research.gla.ac.uk

Abstract

Previous research has shown that there are significant task-switching costs even when participants have time to prepare for task switching after cueing. We investigated individual differences in task switching by monitoring errors and response times of individual participants. In Experiment 1A, 58 participants were encouraged to finish the session early by completing 200 consecutive trials without making an error. In case of a mistake, they had to repeat their effort until the experimental session expired. Using this demanding procedure, 16 participants managed to complete early. Among these 16 we identified 9 best performers who showed no significant switch costs. We conducted follow-up Experiment 1B on these best performers by systematically varying cue-stimulus intervals and inter-trial intervals. The results confirmed that these participants had no significant RT and ER switch costs when they had time to prepare the task between cue and target onset. However, significant switch costs emerged when cue and target stimulus were presented simultaneously. In Experiment 1C, using three classical task-switching paradigms, we compared the best performers with 9 controls who had made frequent errors in Experiment 1A. Although the best performers responded faster and made fewer errors, they only showed reduced switch costs in a pre-cued paradigm that had been extensively practiced. In two other paradigms with simultaneous presentation of cue and target stimulus, best performers had switch costs and showed considerable individual differences similar to the controls. We conclude that there are considerable individual differences in task switching and that smaller individual switch costs are mainly related to efficient task preparation. We speculate that efficient task preparation may be linked to better executive control and general intelligence.

Keywords: Individual differences, task-switching costs, task preparation, executive control, linear mixed models.

1. Introduction

It is a well-established finding that switching between tasks slows responses and increases error rates (Kiesel et al., 2010; Vandierendonck, Liefoghe, & Verbruggen, 2010). This cost of switching can be reduced by longer preparation intervals (e.g., Altmann, 2004), predictable task switches (e.g. Rogers & Monsell, 1995; Monsell, Sumner & Waters, 2003), pre-cueing that informs about the upcoming task at the beginning of each trial (e.g. Meiran, 1996; Meiran, Chorev & Sapir, 2000) and extensive practice of task rules (e.g., Merian et al., 2000; Rogers & Monsell, 1995; Stoet & Snyder, 2007). However, studies consistently reported significant “residual” switch costs (e.g., Meiran et al., 2000; Nieuwenhuis & Monsell, 2002; Rogers & Monsell, 1995; Schneider, 2016, 2017) and these residual switch costs may reflect incomplete reconfiguration processes during task switching.

It has been suggested that there are two separate stages of task reconfiguration in task switching (Mayr & Kliegl, 2003; Rogers & Monsell, 1995; Rubinstein, Meyer & Evans, 2001): an early *goal-reconfiguration stage* that can be triggered as soon as participants are cued about the task, and a second *rule-activation stage* that only starts when the target stimulus is presented. Residual switch costs reflect the second rule-activation stage where participants wait for the target stimulus before they can execute a specific task rule. This account has been supported by a number of recent studies (e.g., Hydock & Sohn, 2011; Weidler & Abrams, 2013). Nonetheless, the assumption that residual switch costs arise from the postponed completion of reconfiguration has been challenged.

According to De Jong’s (2000) *failure-to-engage* account on task-set preparation, participants either prepare for the upcoming task or fail to do so. In trials in which active preparation occurs, the residual switch costs disappear because advance preparation is complete before the target stimulus is presented. In other trials, however, advance preparation is incomplete when the target stimulus is presented, and this may occur even after extended

preparation intervals. Residual switch costs are therefore a consequence of participants who occasionally fail to engage in the preparation process. As De Jong (2000) pointed out, response time distributions of task-switch trials should reflect a mixture of prepared and unprepared processing states (see also Nieuwenhuis & Monsell, 2002; Poboka, Karayanidis, & Heathcote, 2014). This implies that performance in fully prepared task-switch trials should be similar to performance in task-repeat trials. In line with this, Poboka et al. (2014), for example, reported that switch and repeat trials had very similar RT distributions in conditions with long cue-target intervals.

If residual switch costs arise from a failure-to-engage during preparation, then it may be possible to eliminate residual switch costs by improving task preparation. Attempts to eliminate residual switch costs focused on increasing participants' motivation in order to fully engage them in advance preparation. For example, Nieuwenhuis and Monsell (2002) used visual feedback and payoffs after each block in order to reduce response times. In addition, they used blocks of only 16 trials in order to minimize fatigue and to sustain advance preparation throughout each block. Nonetheless, they still found substantial residual switch costs, the difference in mean RTs between switch and repeat trials, of +69 ms.

Another method to reduce residual switch costs was deployed by Verbruggen, Liefvooghe, Vandierendonck and Demanet (2007). They were able to improve participants' task preparation by reducing the cue presentation time. Residual switch costs were smaller and non-significant when the cue was removed after a brief presentation of 96 ms rather than remaining present throughout each trial (see their Experiments 2, 3, and 4). Verbruggen et al. (2007) concluded that by using only a briefly presented cue participants were more likely to process the cue and therefore complete preparation for an upcoming task switch within cue-stimulus intervals (CSIs) of more than one second (see also Experiment 3 in Proctor, Koch, Vu & Yamaguchi, 2008). However, Schneider (2016, Experiment 5) was unable to replicate

the results of Verbruggen et al. (2007) and instead found large and significant residual switch costs when the cue was followed by a mask, similar to a condition where the cue was visible for the entire CSI and remained present after target onset. These contrasting findings suggest that residual switch costs are not just modulated by cue availability during CSIs.

More recently, Schneider (2017) tried to modulate residual switch costs by increasing participants' phasic alertness — a form of attention that is described by rapid and brief changes in sensitivity to external stimulation (Posner, 1978, 2008; Posner & Boies, 1971). Schneider (2017) inserted an alerting stimulus shortly before target stimulus onset in some trials and compared them to trials with no such alert. He found shorter RTs in trials with alert compared to trials without alert, suggesting that general task performance can be improved by increased phasic alertness. However, he found no evidence that phasic alertness reduced residual switch costs.

There are two potential limitations in studies that have tried to remove switch costs (Nieuwenhuis & Monsell, 2002; Schneider, 2016, 2017; Verbruggen et al., 2007). The first limitation is that experimental manipulations in conventional task-switching paradigms may affect participants differently. Previous task-switching research has demonstrated that significant residual switch costs remained despite various attempts to eliminate them. However, the question whether all individuals show switch costs or not has not been addressed? This is similar to the general question posed by Haff and Rouder (2017, 2018): Does everyone show the same effect in a cognitive task? More specifically, in a typical task-switching experiment, do individual participants have the same switch costs? Individual differences in task-switching may be obscured when reporting averaged group performance. There is evidence that some participants learn to switch between tasks better than others, showing striking individual differences in their task-switching performance (Stoet & Snyder, 2003, 2007). More recently, Watson and Strayer (2010, 2012) reported “super-taskers” (2.5%

of the sample) who demonstrated extraordinary high levels of cognitive competence in dual-tasks, and showed more efficient brain activity in the attentional control network (Medeiros-Ward, Watson & Strayer, 2014). These findings challenge previous studies that have tried to eliminate switch costs but only report group performances.

It seems possible that not every participant shows switch costs because participants may have different trait-like switching abilities or may be motivated differently in more demanding experimental settings. We surmised that a few “super-switchers” may be hidden in a larger sample. “Super-switchers”, if they exist, should exhibit minimal or zero switch costs independent of experimental conditions. Moreover, they should outperform others in terms of accuracy. In order to find out whether “super-switchers” exist, we report not only average group performances but investigate individual differences in task-switching performance.

The second limitation of previous studies is that despite successful manipulations of cue presentation times (Schneider, 2016; Verbruggen et al., 2007), alerting stimuli (Schneider, 2017) and feedback (Nieuwenhuis & Monsell, 2002), we cannot be sure that participants processed all task information and exerted the same effort in each trial. Researchers typically assume that participants are fully engaged and motivated but previous results suggest that participants are unable to prepare for the task set in each upcoming trial (Lien, Ruthruff, Remington & Johnston, 2005) and pay more attention to task-set changes in some trials than in others (De Jong, 2000; Lindsen & De Jong, 2010).

In order to motivate participants to prepare the task set in each upcoming trial we used a novel procedure that encourages participants to engage in every single trial for an extended period. In Experiment 1A, participants were asked to finish the experiment early by making no error in a block of 200 consecutive trials with two randomly intermixed tasks. We suggest

that this “zero-error policy” would motivate participants to fully concentrate on the task and reduce "failure to engage".

In summary, the present study sought to investigate how participants differ in their task-switching performance using different tasks, conditions and paradigms, with particular focus on individual task-switching costs.

2. Experiment 1A

Experiment 1A aimed to study individual differences in task-switching using a highly-demanding procedure. In contrast to conventional task-switching experiments with a fixed number of experimental trials, we asked participants to keep trying until they completed 200 consecutive trials in a mixed-task block without committing a single mistake.

Alternatively, testing continued until the experimental session exceeded 90 minutes. We asked participants to keep practicing the tasks for up to 90 minutes as previous studies have found improved switching performance after extended training (Merian et al., 2000; Rogers & Monsell, 1995; Stoet & Snyder, 2007).

We assumed that asking participants to complete the experiment by making no error in 200 trials would heighten participants alertness and motivation over each consecutive trial. In addition, this method provides a series of RT measurements that are not confounded by intermittent errors (Houtman, Castellar & Notebaert, 2012; Regev & Meiran, 2014; Van der Borgh, Braem, Stevens & Notebaert, 2016).

Based on previous research on individual differences in cognitive performance (Haff & Rouder, 2017, 2018; Medeiros-Ward et al., 2014; Stoet & Snyder, 2003, 2007; Watson & Strayer, 2010, 2012), we anticipated that participants would perform differently in task-switching. We expected that a few highly-engaged participants may reach 100% accuracy in

their best-performing block and show no apparent RT switch costs. Other participants may perform more poorly, making frequent errors in the mixed-task block, showing significant switch costs, or both.

2.1. Method

2.1.1. Subjects

We recruited a total of 62 students from the University of Glasgow and Caledonian University. We tried to establish a reasonably large sample that would represent typical task-switching participants including highly-engaged participants and possibly a few “super-switchers”. All participants received a small reward for taking part and were entered into a prize draw to win a £5, £10, or £20. Two participants had to be excluded because they quit the experiment before completing the study. We also excluded two poorly performing participants because they only achieved a maximum of three trials in their mixed blocks. The 14 male and 44 female students in the remaining sample of 58 participants were between 20 and 34 years old ($M = 25.0$ years, $SD = 3.1$). All participants passed a color-blindness test (Ishihara, 1983), and they were naive with respect to the task-switching paradigm and experimental hypotheses.

2.1.2. Apparatus

The experiment was conducted in a quiet and dimly-lit laboratory. Participants were seated in front of a computer screen at a viewing distance of approximately 57 cm. The experiment was programmed using PsyToolkit software (an open access software toolbox for programming psychological experiments based on Linux operating systems; Stoet, 2010, 2017) and run on a PC with a 24-inch screen. In order to improve response time measurement, a Black Box toolkit (BBTK) response pad was used to record button-press

responses with millisecond precision. Two of the four white buttons on the response pad were used to record responses. All data were analyzed in R version 3.4.2 (R Core Team, 2017).

2.1.3. Stimuli and Tasks

We employed a pre-cued color/shape task-switching paradigm. Both cues and stimuli were displayed on a black background. The task cues were displayed at the center of the screen. The cues were white isosceles triangles with side length of 35 mm and base length of 42 mm. A triangle pointing upwards indicated a color task and a triangle pointing downwards indicated a shape task. We used four different rectangles as target stimuli: a vertically elongated (high) red or green bar, a horizontally elongated (wide) red or green bar. The size of the stimuli varied randomly across trials, with the shorter side ranging between 6.6 to 33 mm and the elongated side ranging between 46 to 73 mm. The RGB color of the stimuli also varied randomly across trials (red, green, and blue channels could range between 0 and 255, as is standard in many computer applications). For the red stimuli, the red channel value ranged between 200 and 255 whereas the green channel value equaled blue channel value varying between 0 and 100. For the green stimuli, the green channel value ranged between 200 and 255 whereas the red channel value equaled blue channel value varying between 0 and 100. The purpose of the variation in color and size of the target stimuli was to encourage participants to use general task rules when making responses rather than recalling specific cue-stimulus-response associations from a “lookup table” (Stoet & Snyder, 2003, 2007; Forrest, Monsell & McLaren, 2014). Participants used the same pair of response keys for both tasks (see Figure 1) resulting in congruent and incongruent trials. In congruent trials, both task-relevant and task-irrelevant target features lead to the same (correct) response in both tasks. In incongruent trials the distracting target features, if erroneously attended to, would result in a slower or incorrect response (cf., Kiesel, Wendt & Peters, 2007).

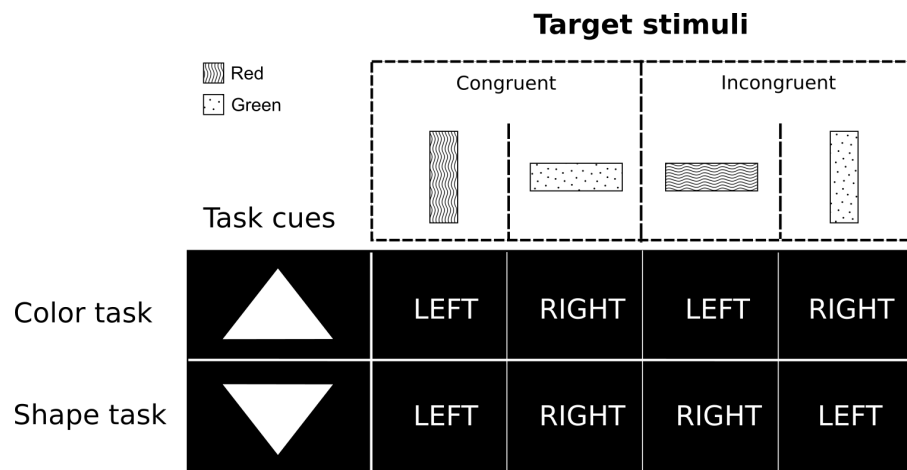


Figure 1. Illustration of the task rules in the color/shape task-switching paradigm of Experiment 1A. The color task cue was a white triangle pointing upward, and the shape task cue was a white triangle pointing downward. The target stimuli were four rectangular bars (color = red, green; shape = high, wide). LEFT and RIGHT corresponds to pressing the left and right button on the response pad, respectively.

2.1.4. Procedure

An experimental session lasted up to 90 minutes. Before testing, each participant received verbal and written instructions that introduced the task rules for the color and shape task and how they were cued (Figure 1).

Each trial started with the presentation of a task cue signaling the relevant task that had to be performed (Figure 2). The cue was shown for 250 ms before it was covered by a mask for 250 ms followed by a blank screen for 150 ms. Altogether the cue-stimulus interval (CSI) lasted 650 ms. The mask could help participants to focus on the cue and to initiate task preparation before the target stimulus was presented. The procedure with cue masking was similar to Verbruggen et al. (2007) and Schneider (2016). Immediately after the CSI, a target stimulus appeared and remained on screen until the participant gave a response or until the maximal RT of 1,500 ms was exceeded. A correct response would trigger the next trial after an inter-trial interval (ITI) of 500 ms. If participants failed to respond within 1,500 ms, the

message “Too slow” appeared for 2,000 ms. If participants pressed the wrong key, an error warning was displayed for 2,000 ms. At the end of each block or after an incorrect response, each participant received individual feedback indicating their mean RTs and the number of consecutive correct trials.

Participants were asked to fully engage in the experiment with the incentive to finish early if they made no error in 200 consecutive trials of the mixed-task block. Once a participant gave the wrong response or did not respond in time (counted as incorrect) in the mixed-task block, the attempt of reaching zero errors was aborted and the participant would receive practice trials in the color and the shape task for additional task-rule practice. The experiment lasted until a participant performed 200 consecutive trials in the mixed-task block without mistakes. In case a participant did not manage to reach zero errors, the experiment was terminated after 90 minutes.

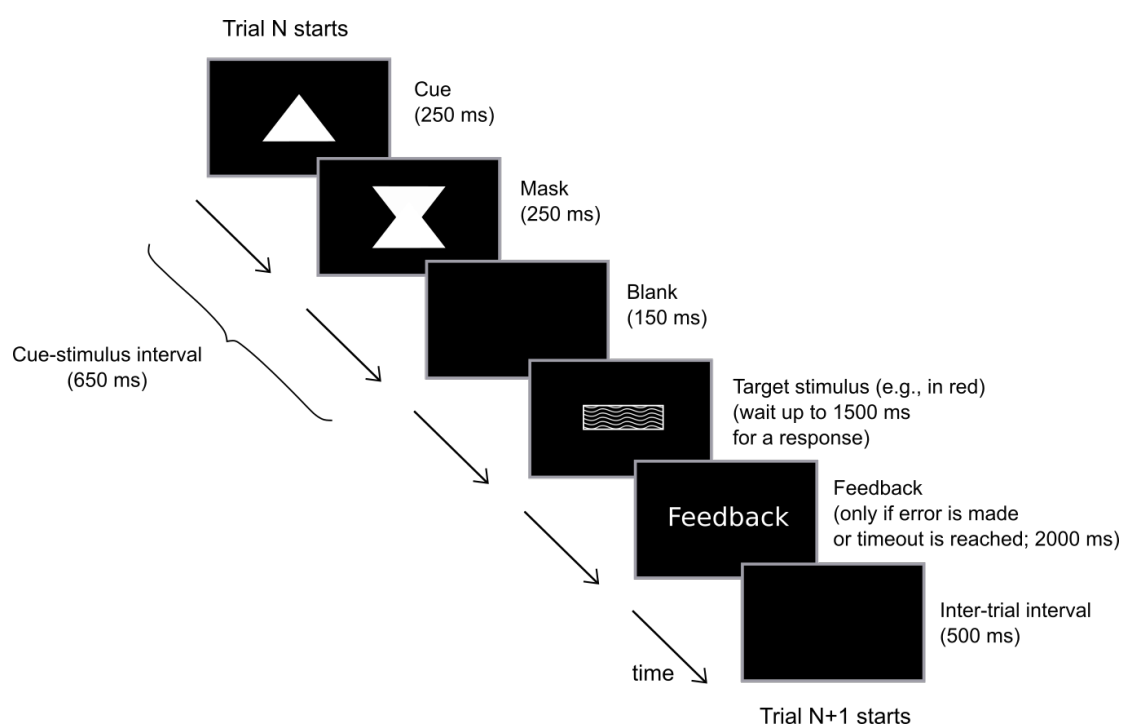


Figure 2. Experiment 1A. Schematic timeline of a trial in the color/shape mixed-task block.

2.2. Results

We examined individual differences in task switching using a novel procedure that encouraged participants to make zero mistakes. We first conducted conventional ANOVAs on response times (RTs) and error rates (ERs) averaged across conditions from all mixed blocks. In addition, we employed Generalized Linear Mixed-effects Models (GLMMs; Bolker et al., 2009) using the gamma link-function in order to study individual differences in RTs from the mixed-task block with the maximum number of responses (MAX block). Each individual can have a different number of trials in their MAX block. GLMMs can take into account imbalanced data and typically provide better model fits than conventional ANOVAs. In order to guard against model overfitting we employed information criteria (AIC, BIC) that penalize more complex models. The fixed effects of a GLMM reflect group-level performance whereas random effects reveal individual variability in RTs. We hypothesized that participants may vary in their task-switching performance, particularly in the MAX blocks, since participants may be differently motivated.

2.2.1. Mean RTs and ERs from All Mixed Blocks

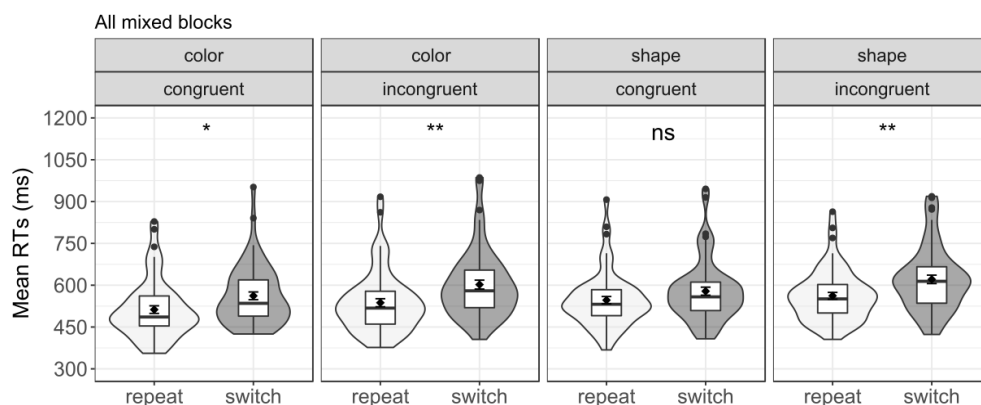
The first trial of each block was discarded from the analyses because it cannot be classified as a switch or a repeat trial. Error trials were also excluded from the RT analysis. Since participants had to start a new block whenever they made an error, it was not necessary to exclude trials after an error. Mean RTs and ERs for each participant (see Figure 3) were entered into separate three-way ANOVAs with repeated measurements on factor Task (color, shape), Trial transition (repeat, switch) and Congruency (congruent, incongruent).

For mean RTs, we observed three statistically significant main effects. There was a significant main effect of Task, $F(1, 57) = 22.30, p < .001, \eta^2_p = .28$. Participants responded on average more slowly in the shape task (577 ms) than in the color task (553 ms). In

addition, there was a significant main effect of Congruency, $F(1, 57) = 30.69, p < .001, \eta_p^2 = .35$, with slower mean responses for incongruent trials (581 ms) compared to congruent trials (550 ms).

More importantly and in line with previous findings, we found a statistically significant main effect of Trial transition, $F(1, 57) = 76.53, p < .001, \eta_p^2 = .57$. Responses were slower in trials with task-switching (591 ms) compared to trials with task repetition (540 ms), indicating an average RT switch cost of +51 ms. The switch cost was larger in the incongruent trials ($SC = \text{switch} - \text{repeat} = +61 \text{ ms}, p < .001$) than in the congruent trials ($SC = +41 \text{ ms}, p = .015$), indicating a statistically significant interaction between Trial transition and Congruency, $F(1, 57) = 5.99, p = .018, \eta_p^2 = .10$. No other interaction effects were statistically significant.

For ERs, we found a significant main effect of Congruency, suggesting more errors in incongruent trials (8.08%) than in congruent trials (2.62%), $F(1, 57) = 43.63, p < .001, \eta_p^2 = .43$. As in the RT analysis, we found a statistically significant main effect of Trial transition, suggesting more errors in switch trials (6.26%) than in repeat trials (4.44%), $F(1, 57) = 13.08, p < .001, \eta_p^2 = .19$, indicating a significant ER switch cost of +1.82%. The ER switch costs were larger in the incongruent condition ($SC = +3.52\%, p < .001$) than in the congruent condition ($SC = +0.13\%, p = .904$), $F(1, 57) = 10.37, p = .002, \eta_p^2 = .15$. No other effects reached statistical significance.



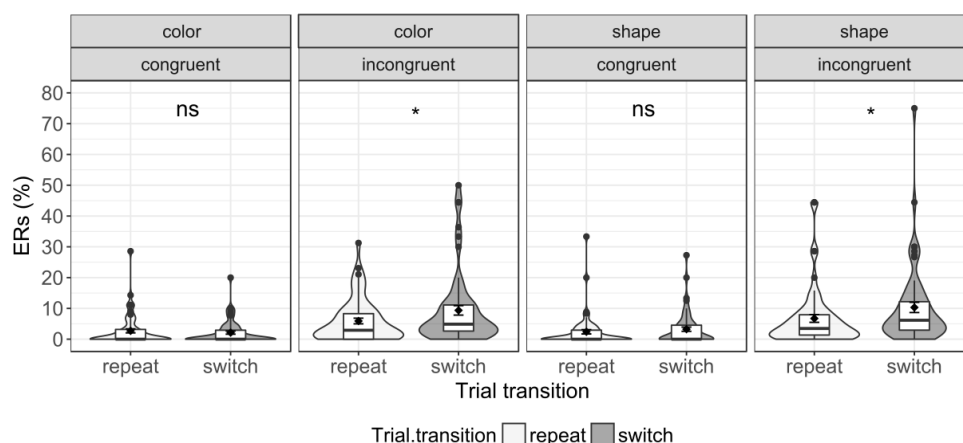


Figure 3. Results of Experiment 1A averaged across all mixed blocks. Mean RTs (top panels) and ERs (bottom panels) for Task (color, shape), Trial transition (repeat, switch) and Congruency (congruent, incongruent). Violin plots with superimposed boxplots show averaged data of $N = 58$ participants. Each violin plot represents the estimated distribution of mean data in the corresponding condition. Bold horizontal bars and boxes denote medians and interquartile ranges, respectively. Black dots represent outliers whereas black diamonds and error bars denote means and standard errors, respectively.

Note: ** $p < .01$; * $p < .05$; ns = non-significant

The results of the ANOVAs indicate that significant RT and ER switch costs occurred, even though participants were asked to make no errors. However, it is likely that most participants only fully engaged in the mixed block where they achieved their maximum number of consecutive correct responses. Therefore, we considered only performance in the MAX blocks in the following analysis. We tried to identify how participants differed in their best-performing block (i.e., the MAX block): Did some participants perform better than others, e.g., by not making a single error in their MAX block? Did individuals who were fully engaged and highly motivated in their MAX block also have zero switch costs?

2.2.2. MAX Blocks

Participants had different numbers of correct trials in their MAX block (Appendix A). Only a few valid observations were available for poorly performing participants but up to 200 observations for some exceptional participants, leading to imbalanced numbers of observations across conditions ($M = 109$ trials, ranging between 5 to 200 trials). Similarly, the individual analyses of RT switch costs showed that individual switch costs ranged between -75 ms to +251ms, with an average switch cost of +35 ms in the MAX block (Appendix A).

2.2.2.1 Best-performing participants in MAX blocks

We found that after an average practice of 1,233 trials (ranging from 540 to 1,956) before the MAX block, a total of 16 participants from our sample were able to finish the experiment early by completing 200 consecutive trials in the MAX block without making a single error. Among the 16 participants, we identified 9 *best-performing participants* or *best performers* who learned to switch between tasks without error after relatively few trials (mean number of trials before MAX = 1,102 trials, ranging from 540 to 1,656 trials). Each of these 9 participants had no significant RT differences between task-switch and task-repeat trials (mean switch cost of +5 ms). For comparison, the remaining 7 participants, who also made no errors in the MAX block, responded more slowly in task-switch than in task-repeat trials (mean switch cost of +42 ms). Note that among these 7 participants, a two-sample *t*-test showed that Participant 7 performed significantly faster in task-switch trials compared to task-repeat trials showing a negative switch cost of -48 ms ($p = .011$, Cohen's $d = .37$). We did not consider Participant 7 as one of the best performers in the present study because we aimed to identify participants who would show the same accuracy and speed in task-switch as in task-repeat trials.

In order to study whether the 9 best-performing participants varied in RTs over the course of their MAX block, we split the 200 trials from their MAX blocks into the first and

second 100. The corresponding averaged RT data were then submitted to a four-way repeated-measure ANOVA with factor Trial transition (task-repeat, task-switch), Congruency (congruent, incongruent), Task (color, shape) and Block half (first, second). The results showed non-significant main effects of Trial transition ($F < 1$) and Congruency ($F = 3.67, p = .092$). Best performers showed non-significant switch costs (+5 ms) and congruency effects (+13 ms). Importantly, the results indicated non-significant effects involving Block half, suggesting that the 9 best-performing participants showed non-significant change in RTs between the first and the second half of the MAX blocks. The switch costs were +7 ms in the first half and +4 ms in the second half. The congruency effects were +8 ms in the first half and +18 ms in the second half.

2.2.2.2. RT analyses and individual differences in MAX blocks

In order to study RTs and individual task-switching performance in MAX blocks, we employed Generalized Linear Mixed-effects Models (GLMMs). Although participants had different numbers of responses in their MAX block, hierarchical models can accommodate imbalanced RT data and provide estimates of group-level fixed effects as well as individual random effects (Baayen, Davidson & Bates, 2008). The latter can capture individual differences in task-switching performance.

We tested models with full factorial design (fixed effects for Task, Congruency and Trial Transition, and their interactions) and identified the most parsimonious model that converged (GLMM 1A.2 in Appendix B). This model had by-subject random effects for mean RT (intercepts), Trial transition (slopes) and Task (slopes).

In order to report p -values for fixed effects, we used the asymptotic Wald test where each “ t value” is computed as a ratio between estimated and standard error. In the following we report these t -values and the corresponding p -values without degrees of freedom (Bates

et al., 2015). The fixed effects of the GLMM in Experiment 1A suggest that responses were 24 ms slower in the shape task (598 ms) compared to the color task (574 ms), $t = 6.52$, $p < .001$; 28 ms slower in switch trials (600 ms) compared to repeat trials (572 ms), $t = 5.85$, $p < .001$; and 18 ms slower in the incongruent condition (595 ms) compared to the congruent condition (577 ms), $t = 6.18$, $p < .001$. The two-way interaction between Task and Trial transition was statistically significant ($t = -2.75$, $p = .006$), suggesting larger switch costs when switching to the color task (+34 ms) than switching to the shape task (+23 ms). There also was a statistically significant three-way interaction between Task, Trial transition and Congruency ($t = 2.69$, $p = .007$), suggesting that switch costs were larger in the color-congruent condition (+37 ms), compared to the color-incongruent condition (+30 ms), the shape-incongruent condition (+25 ms) and the shape-congruent condition (+20 ms).

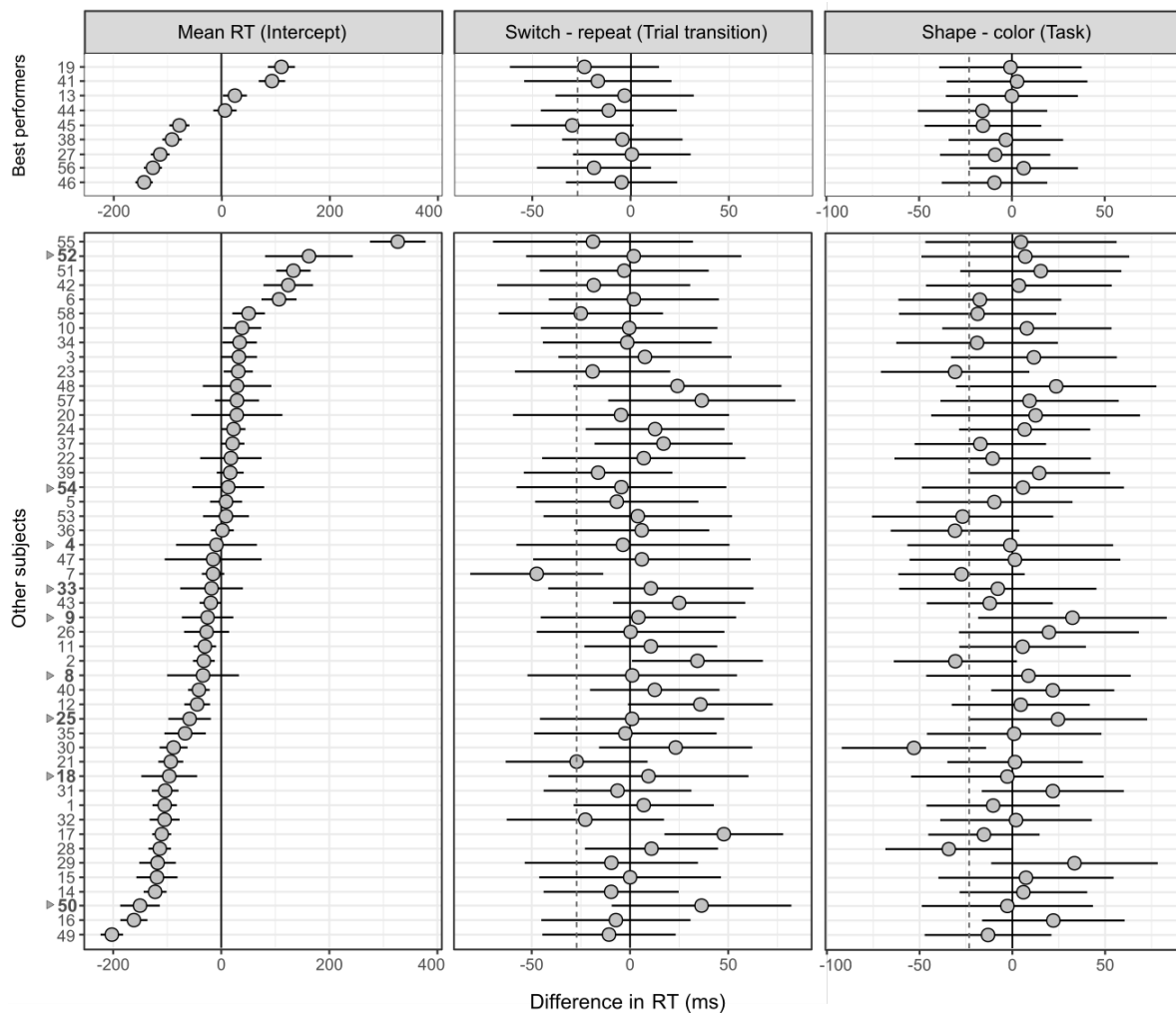


Figure 4. Experiment 1A. Illustration of by-subject random effects for RTs. Subject numbers on the left identify individual participants. Dotplots in the three top panels show random intercepts and random slopes of the best performers (no errors and non-significant switch costs), and the dotplots in the three bottom panels illustrate the random effects of the other participants/subjects. Dotplots in the left column illustrate individual deviations (dots) and 95% confidence interval (horizontal error bars) from the estimated mean RT of the $N = 58$ participants. The dotplots in the middle and right column show individual deviations from the fixed effect of Trial transition and Task (random slopes). The solid vertical lines centered on zero in the left, middle and right panels correspond to the estimated mean RT (Intercept = grand mean RT of 586 ms), mean switch cost (Trial transition; switch - repeat = +28 ms), and mean task difference (Task; shape - color = 24 ms), respectively. The dashed vertical line in

the middle and right plot indicate zero switch cost and zero task difference, respectively. Please note the differently scaled *x*-axes (in ms) in the left and right panels.

Figure 4 illustrates that participants varied considerably in their mean RTs (Intercepts) from the overall average. Participant 49, for example, was on average 203 ms faster and Participant 55 was 327 ms slower than the grand average RT in the sample (586 ms). The 9 best-performing participants also showed a considerable spread in their mean RTs. For example, Participant 46 responded significantly faster and Participant 19 responded significantly slower than the total average.

The individual differences in RT switch costs (Trial transition), however, were less pronounced and appeared to be independent of individual RTs (Pearson's $r = -.07$). We found clear deviations from the group-average switch costs of +28 ms in only 3 out of 58 participants: Participant 7 (-47 ms), Participant 2 (+34 ms), and Participant 17 (+48 ms). Not surprisingly, the 9 best-performing participants (Figure 4; top middle panel) showed smaller switch costs deviating only marginally from the mean switch cost (solid vertical line) and none of them deviated significantly from zero switch costs (dashed vertical line). In comparison, 12 out of 49 other participants (Participant 2, 11, 12, 17, 24, 28, 30, 37, 40, 43, 50, and 57) showed switch costs that were significantly larger than zero.

Similarly, the individual differences in RT task-difference showed a random pattern and appeared to be independent of individual RTs (Pearson's $r = .02$) as well as individual switch costs (Pearson's $r = -.02$). None of the best-performing participants showed a significant difference between color and shape tasks and only five of the other participants (Participant 9, 16, 29, 31, 40) showed a significant difference between color and shape tasks.

2.3. Discussion

Experiment 1A investigated individual differences in task switching using a novel experimental procedure. We conducted both conventional ANOVAs and mixed-effect models to study their task-switching performance. We observed a significant RT switch cost of +51 ms averaged across all trial conditions, mixed blocks, and participants. However, RT switch costs were reduced to +28 ms in the MAX block. We attribute the reduction in the task-switch costs to increased engagement and motivation, possibly relating to more efficient task-switching strategies in the MAX blocks. It may be argued that switch costs in the MAX blocks and in all mixed blocks were relatively small compared to other task-switching studies. Schneider (2017), for example, found significant switch costs of +128 ms for a response-time limit of 2,500 ms. With a narrower response window of 1,500 ms, our participants experienced more time pressure and were more motivated to respond faster in each trial. This may have attenuated RT differences between switch and repeat trials.

We studied individual performances in MAX blocks in order to identify participants who maximally engaged in task switching over many consecutive trials. We found that 16 participants managed to complete the experiment early by making no error in 200 consecutive trials in the mixed-task block (100% accuracy). Among these 16 participants, 9 (about 15% of the total sample) showed non-significant RT switch costs. We labelled these high-performing individuals as *best performers*. The other participants made an error and/or showed significant switch costs in their MAX block, even after practicing the tasks for over an hour. Surprisingly, Participant 7 showed a negative RT switch cost. This participant might have employed a strategy that led to faster responses in task-switch compared to task-repeat trials.

As expected the GLMM on RTs in the MAX block indicates individual differences in task-switch costs although the differences were relatively small throughout our sample of

participants. It appears that the best performers showed task-switching characteristics that were comparable to most other participants. However, the task-switching procedure in Experiment 1A was extremely demanding as it encouraged the highest level of accuracy (100% accuracy). A participant who completed the 200 trials without making a single mistake had to maintain full attention. Therefore the 9 best performers were quite exceptional because they were not only 100% accurate in their switching performance over 200 trials, but also performed task-switch trials as quickly as task-repeat trials. According to the *failure-to-engage* account (De Jong, 2000; Lindsen & De Jong, 2010), these participants were able to fully engage in each upcoming trial for an extended period of time. In contrast, other participants seemed less capable during task-switching. They occasionally failed to engage in the task and therefore made mistakes and/or showed significant switch costs in their MAX block.

The identification of best performers supports previous studies on individual differences in task-switching (Stoet & Snyder, 2003, 2007), multi-tasking (Medeiros-Ward et al., 2014; Watson & Strayer, 2010, 2012) and related cognitive tasks (Haff & Rouder, 2017, 2018). In these studies some participants learned tasks better than others, suggesting superior cognitive abilities or higher motivation.

It is possible that the best-performing participants also had superior cognitive control. In an additional ANOVA we split the MAX block into the first and last 100 trials. The results indicated that these participants did not show significant switch costs or even congruency effects in either half. Previous research suggested that reduced switch costs may reflect high-level task engagement (Lindsen & De Jong, 2010; De Jong, 2000), and reduced congruency effect may reflect better control of attention that is maintained across trials (Bugg & Braver, 2016). We conclude that the best performers were highly engaged in each trial for an extended period demonstrating better cognitive control.

It is also possible that by using a novel experimental procedure where participants were encouraged to make no mistake, best performers were more strongly motivated by the zero-error policy. In order to investigate whether the best performers also show exceptional switching performance in more conventional task-switching paradigms, where participants are allowed to make mistakes, we invited the best performers to take part in follow-up Experiment 1B. We tried to establish “super-switchers” among the best performers. “Super-switchers” should show higher accuracy and no switch costs, independent of experimental conditions. In a second follow-up, Experiment 1C, we compared the 9 best performers with 9 control participants who had made frequent errors in Experiment 1A.

3. Experiment 1B

Experiment 1B was designed as a follow-up on the best-performers in Experiment 1A. We sought to study the switching abilities of the best performers by using the same color/shape tasks in a more conventional experimental setting where participants can make mistakes without having to start again. In particular, we investigated the cue-stimulus interval (CSI) and inter-trial interval (ITI) as critical factors that may affect the task-switching performance of the best performers. We tried to identify “super-switchers” among the best performers - individuals who would show superior task-switching performance across different conditions and paradigms.

Experiment 1A had a fixed CSI of 650 ms and a fixed ITI of 500 ms in every trial. It therefore remained unclear whether CSI or ITI was critical for their task-switching performance. According to both the *FTE* account and the task-set reconfiguration account, the CSI is considered as more important for reducing residual switch costs because task-set reconfiguration occurs during this interval (De Jong, 2000; Mayr & Kliegl, 2003; Poboka et

al., 2014; Rogers & Monsell, 1995). One possible explanation for the reduced switch costs is that best performers may be more efficient in their advance preparation during the CSI.

According to the proactive interference account, residual switch costs should be reduced for longer ITIs because interference from a previous task set decays gradually over time (Allport, Styles & Hsieh, 1994; Meiran et al. 2000; Koch & Allport, 2006; but see Horoufchin, Philipp & Koch, 2011; Grange, 2016). This leads to the alternative explanation that interference may have decayed more quickly in the best performers. It is also possible that both accounts play a role in task-switching because switch costs can be the result of both preparation and interference from the previously executed task set (Vandierendonck et al., 2010).

We sought to investigate these possibilities in the best performers by systematically varying the CSI from 0 to 650 ms and the ITI between 150 ms and 500 ms in different blocks. We made three predictions. First, we predicted that a longer CSI (650 ms) and a longer ITI (500 ms) in Experiment 1B should result in no significant switch costs in best performers, replicating their individual results in Experiment 1A. Second, according to the *failure-to-engage* and the task-set reconfiguration account we predicted that the task-switching performance should be significantly impaired if the CSI was reduced from 650 ms to 0 ms. Similarly, according to the proactive interference account, we predicted increased task-switching costs if the ITI was reduced from 500 ms to 150 ms. Third, we postulated that “super-switchers” should be resilient to these changes, showing no errors and no switch costs independent of the manipulation of CSI and ITI.

3.1. Methods

3.1.1. Subjects

Nine participants who were identified as the best performers in Experiment 1A (3 males, 6 females) were invited back to take part in this follow-up experiment approximately one month later. Participants were paid £10 each for taking part.

3.1.2. Apparatus and stimuli

All aspects of the stimulus presentation were identical to the color/shape task-switching paradigm as used in Experiment 1A, except for a change of the task cue in the two composite conditions without CSI. In the conditions without CSI, the filled white triangles (30 mm each side) were replaced by a bigger isosceles triangle with a base length of 29 cm and side lengths of 24 cm. In each trial, both the cue and the target stimulus were located at the center of the screen. The target stimulus always appeared inside a triangle which served as the task cue.

3.1.3. Procedure

Different from the color/shape paradigm used in in Experiment 1A, both cue-stimulus interval (CSI: 0, 650 ms) and inter-trial interval (ITI: 150, 500 ms) were systematically manipulated within participants leading to four task-switching conditions: Condition 650-500, 650-150, 0-500, and Condition 0-150 (see Figure 5). In a pilot study we found that performing in the conditions with CSI 650 ms before the condition with CSI 0 ms helped participants to better recall the task rules, reducing the error rates in the more difficult Condition 0-500 and 0-150. The entire experiment lasted approximately 1 hour. In each condition, there was a block of 50 trials with the color task, then a block of 50 trials with the shape task, followed by a block of 200 trials with randomly mixed tasks. Participants always completed the two single-task blocks to practice the task rules before starting the mixed-task blocks. In this experiment, the zero-error policy was not applied because we wanted to study participants' performance in a more conventional task-switching paradigm.

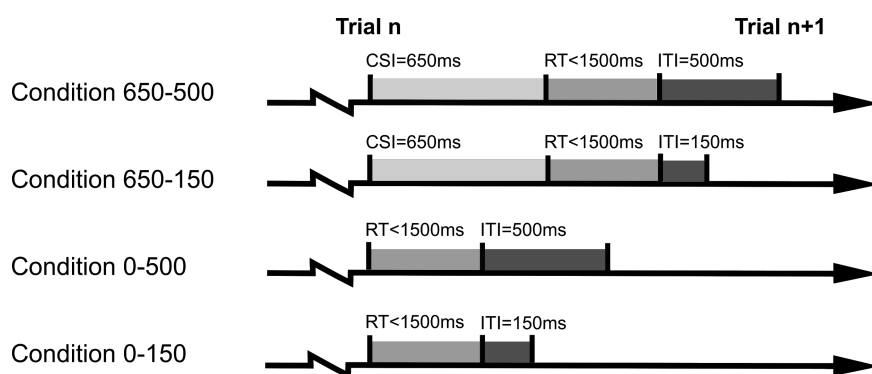


Figure 5. Experiment 1B. Schematic depiction of the four combinations of cue-stimulus interval CSI (CSI 650 ms, 0 ms) and inter-trial interval (ITI 500 ms, 150 ms) in the color/shape task-switching paradigm.

3.2. Results

The first trial of each mixed-task block, error trials and the trial following an error were excluded from the RT analysis. In contrast to Experiment 1A where the mixed block expired once an error was made, in Experiment 1B all trials that immediately followed an error were excluded because it is not possible to classify them as task-switch or task-repeat trials. We also excluded trial *n* if it had the same cue-stimulus combination as the preceding trial *n* - 1 because in the conditions with CSI 0 ms cue and the target stimulus were presented simultaneously and a participant could simply repeat the same response as previous trial without cognitive processing of the task. After exclusion of these trials, the number of valid trials ranged between 665 and 794 per participant, with 156 to 199 RT measurements in each condition. We first conducted a conventional ANOVA on mean RTs and ERs. In addition, we applied GLMMs to capture individual differences among the best-performing participants.

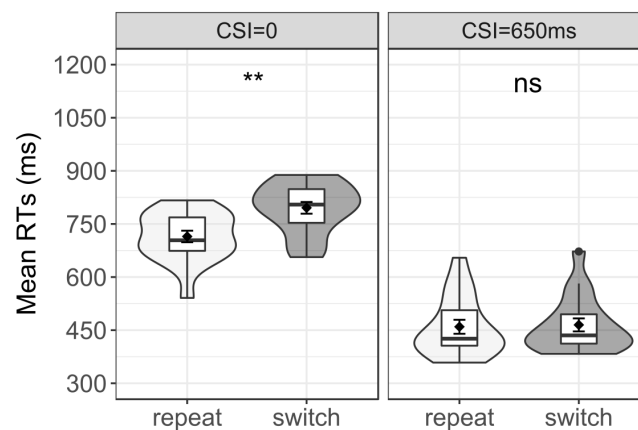
3.2.1. Mean RTs and ERs

Mean RTs and ERs are depicted in Figure 6. They are collapsed across ITIs which had no significant effects on performance (see Appendix A for all conditions). RTs and ERs were analyzed separately using a three-way ANOVA with repeated measures on factor Trial

transition (task-repeat, task-switch), CSI (0 ms, 650 ms), and ITI (150 ms, 500 ms). There was a significant main effect of CSI, $F(1, 8) = 271.75, p < .001, \eta^2_p = .97$, with longer mean RTs for CSI 0 ms (755 ms) compared to CSI 650 ms (462 ms). There was a significant main effect of Trial transition, $F(1, 8) = 34.54, p < .001, \eta^2_p = .81$, with longer mean RTs for task-switch trials (630 ms) than task-repeat trials (587 ms), participants showing a significant RT switch cost of +43 ms.

More importantly, we observed that the RT switch costs decreased by 76 ms when the CSI was increased from 0 (+81 ms, $p = .004$) to 650 ms (+5 ms, $p = .833$), indicating a significant interaction between Trial transition and CSI, $F(1, 8) = 12.55, p = .008, \eta^2_p = .61$. No statistically significant effects associated with ITI were found ($F < 1$ for all effects associated with factor ITI).

Error rates, collapsed over ITIs, are shown in the panels at the bottom of Figure 8 (see Appendix A for all conditions). We did not observe any statistically significant effects for ERs. This shows that best performers were relatively successful at maintaining a constant ER across trials and conditions, suggesting that effects of RTs are not confounded by accuracy.



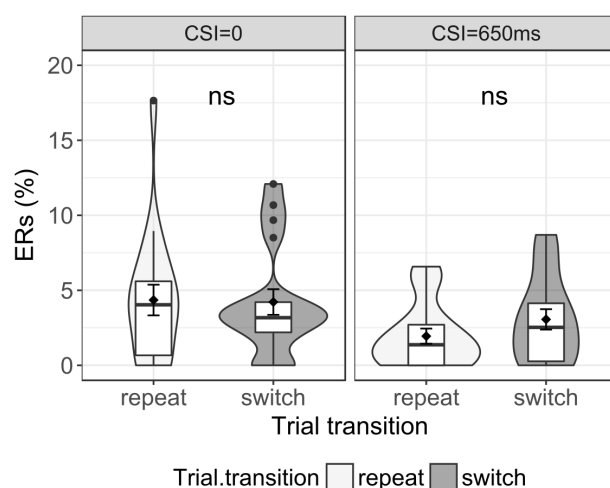


Figure 6. Experiment 1B. RTs (top panel) and ERs (bottom panel) are shown in separate box/violin plots for repeat and switch trials across CSIs (0 ms, 650 ms). Black dots represent outliers whereas black diamonds and error bars denote means and standard errors, respectively.

Note. $**p < .01$, *ns* = non-significant.

Similar to Experiment 1A, we split the trials in the mixed block into two halves and analyzed the RT data accordingly. The corresponding RT data were then submitted to a four-way repeated-measure ANOVA with factors Trial transition (task-repeat, task-switch), CSI (0 ms, 650 ms), ITI (150 ms, 500 ms) and Block half (first, second). Again, we found a significant interaction between Trial transition and CSI, $F(1, 8) = 16.66$, $p = .004$, $\eta^2_p = .68$. Participants did not show significant RT switch costs in the condition with CSI 650 ms, but showed significant costs in the condition with CSI 0 ms. Block half did not significantly interact with Trial transition ($F < 1$) and CSI ($F = 1.63$, $p = .237$). We did not find a significant three-way interaction between Trial transition, Block half and CSI ($F < 1$), suggesting that switching performance did not differ between the two halves of the block. For CSI 650 ms, switch costs were +7 ms in the first half and +6 ms in the second half. In

contrast, for CSI 0 ms RT switch costs were +95 ms in the first half and +83 ms in the second half. No other effects reached statistical significance.

3.2.2. Individual Differences

We conducted GLMMs to capture individual differences among the best-performing participants. The raw RT data were modelled by gamma distributions in a full factorial design for fixed effects and different by-subject random effects. We identified the most parsimonious model (see GLMM 1B.3 in Appendix B). Trial transition, CSI and ITI, and all interactions were entered as fixed effects. The intercept, the main effect of CSI and ITI and the interaction between CSI and Trial transition featured as by-subject random effects.

The fixed effects are consistent with the ANOVA results and are summarized in Appendix B. Responses were significantly faster in CSI 650 ms (471 ms) compared to CSI 0 ms (762 ms), $t = -92.58$, $p < .001$. RT switch costs were smaller for CSI 650 ms (+4 ms) compared to CSI 0 ms (+79 ms), $t = -20.80$, $p < .001$. Moreover, there were no significant differences between switch costs for ITI 150 ms (+40 ms) and ITI 500 ms (+43 ms), $t = 0.92$, $p = .360$.

The by-subject random effects explained considerable variance. The top panel of Figure 7 shows large individual deviations from the grand mean RT (Intercept). When comparing Figure 4 with Figure 7 regarding mean RTs (Intercepts), we found that most best performers were consistent in their mean RTs across experiments. For example, Participant 46 was the fastest best-performer in Experiment 1A as well as 1B. Participant 19 and 41 who were the slowest best-performers in Experiment 1A were again slower in the present experiment. However, Participant 13 who was slightly slower in Experiment 1A performed faster in the present experiment.

The bottom panel of Figure 7 shows individual deviations between different CSIs and ITIs. Participant 38 and 45 showed improved RT performance when the CSI was increased to

650 ms, while Participant 19, 41, and 46 showed less improved performance. Participant 41 and 45 showed faster responses in ITI 500 ms than in ITI 150 ms, while other participants performed more slowly in ITI 500 ms.

Figure 7 also shows individual differences in RT switch costs (middle panels). Participants showed different deviations from the mean switch costs (solid vertical line) and zero switch costs (dashed vertical line) in the CSI 650 ms and in the CSI 0 ms condition. Seven participants did not significantly deviate from zero switch cost in the CSI 650 ms condition whereas Participant 13 and 46 had switch costs significantly higher than zero. In contrast, all participants had switch costs significantly higher than zero in the CSI 0 ms condition.

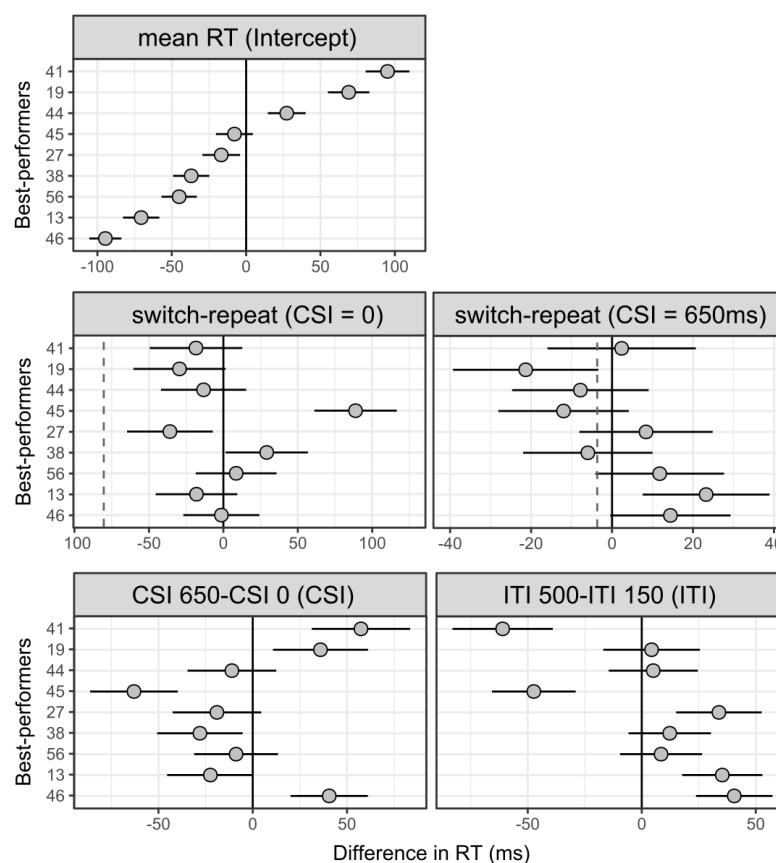


Figure 7. Experiment 1B. Illustration of by-subject random effects. Subject IDs on the left correspond to the Subject IDs in Experiment 1A. Top panel: Dotplot illustrates individual deviations (dots) and 95% confidence intervals (horizontal error bars) from mean target RT

(Intercept = group-average target RT of 617 ms, indicated by the solid vertical lines centered on zero). Middle panel: Dotplots illustrate individual deviations (dots) and 95% confidence intervals (horizontal error bars) from the mean switch costs in CSI 650 ms (+4 ms) and CSI 0 ms (+79 ms) collapsed over ITIs. The dashed vertical lines in the plots of the middle panel indicate zero switch cost in each condition. Bottom panel: Dotplots illustrate individual deviations (dots) and 95% confidence intervals (horizontal error bars) from the main effect of CSI (mean RT in CSI 650 ms - mean RT in CSI 0 ms = -292 ms,) and ITI (mean RT in ITI 500 ms - mean RT in ITI 150 ms = +7 ms). Please note the different RT scales on the x-axes across plots.

3.3. Discussion

The results of Experiment 1B show that on average the best performers developed RT switch costs when the CSI was reduced to 0 ms but showed non-significant switch costs for both RTs and ERs when the CSI was 650 ms, confirming the results in Experiment 1A. This finding is in line with studies that identified preparation effects on task-switching costs (Merian et al., 2000; Altmann, 2004; Schneider, 2016, 2017). However, in none of these studies switch costs were eliminated even when preparation intervals were longer than 2,000 ms (e.g., Meiran et al., 2000). Here, the best performers prepared very efficiently within a CSI of 650 ms, showing no significant switch costs except for Participant 13 and 46.

Importantly, the best performers were only affected by CSI. An increase of ITI from 150 ms to 500 ms did not improve their switching performance. This is inconsistent with the proactive interference account where longer ITIs should lead to reduced switch costs (Allport et al., 1994; Meiran et al. 2000; Koch & Allport, 2006; but see Horoufchin et al., 2011; Grange, 2016). We conclude that the reduced switch costs in best-performers can be attributed to efficient task preparation during CSIs.

Why can best performers prepare more efficiently for a task or reconfigure a task set during relatively short CSIs whilst other participants cannot? In the present experiment, best performers showed reduced switch costs, even without the zero-error policy. This result seems to suggest that the best performers maintained superior switching abilities independent of the zero-error policy. However, not all best performers showed trait-like switching abilities. For example, Participant 13 and 46 varied considerably in terms of switch costs between Experiment 1A and 1B. Since many other participants in Experiment 1A also performed well, showing no mistakes or non-significant switch costs in their MAX block, we need further evidence that sets apart best performers from other participants.

In order to address this question we studied best performers in different task-switching paradigms. Yehene and Meiran (2007) suggested that participants should exhibit general task-switching abilities across paradigms. Experiment 1C was conducted to compare the general task-switching abilities of best performers with a control group.

4. Experiment 1C

The purpose of this follow-up experiment was to compare the best-performers with a control group in conventional task-switching paradigms using different tasks and without applying the zero-error policy. We hypothesized that best performers may have better trait-like switching abilities if they show significantly smaller or even no switch costs across different tasks and conditions compared to controls.

In addition, we employed Raven's advanced progressive matrices (APM, Raven, Raven & Court, 1998) in order to test whether both groups of participants differed in general intelligence. Studies suggested that general intelligence affects the efficacy of cognitive control (Benedek, Jauk, Sommer, Arendasy & Neubauer, 2014; Friedman et al, 2006) which

plays an important role in task-switching. We therefore hypothesized that group differences in task switching may be related to group differences in general intelligence.

4.1. Methods

4.1.1. Subjects

Nine best-performing participants (3 males and 6 females, $M = 23.89$ years, $SD = 1.96$) were invited to take part in this follow-up experiment approximately two months after Experiment 1A. We also invited 9 other participants from Experiment 1A as controls (1 male and 8 females, $M = 23.00$ years, $SD = 1.80$). The control participants are highlighted by an open triangle next to the Subject ID in Figure 4. We did not select the worst-performing participants as controls because they might not sufficiently engage in each trial. The participants in the control group matched the best performers in terms of mean RTs (Intercepts; see Figure 4) but made frequent mistakes even though they had practiced the color/shape task in thousands of trials ($M = 1,626$ trials, ranging from 1,137 to 2,215 trials) in Experiment 1A. They had a MAX of less than 50 trials ($M = 13$ trials, ranging from 10 to 45 trials) in their experimental session over 90 minutes. Participants were paid £10 each for taking part.

4.1.2. Apparatus, tasks and stimuli

The apparatus for stimulus presentation and response collection was identical to Experiment 1A and 1B.

Color/shape paradigm. All aspects of the color/shape task-switching paradigm were the same as in Experiment 1A, except that we did not apply the zero-error policy.

Shape/filling paradigm. The shape/filling task was the same as the task used by Stoet, O'Connor, Conner and Laws (2013, Experiment 1). In the shape task, participants were asked to press a left button if a diamond-shaped target appeared (30.7 mm each side) and a right

button if a square-shaped target appeared (30.7 mm each side), ignoring the dots inside. In the filling task, participants were asked to press the left button for two vertically arranged dots and the right button for three vertically arranged dots, ignoring the surrounding shape. All stimuli were printed in yellow and presented on the top or bottom of a rectangular yellow frame (70 × 80 mm). Participants responded to the surround shape when the target was presented in the upper part of the frame and responded to the filling dots when the target was presented in the lower part. The “Shape” and “Filling” cues were visible throughout each trial to remind participants of the currently relevant task. The inter-trial interval was 800 ms.

Letter/number paradigm. The letter/number task was the same as the task used by Rogers and Monsell (1995, Experiment 1). Participants received a letter/number pair in each trial. The task was to either categorize the letter as a vowel or consonant, or to categorize the digit as being odd or even. The odd numbers were drawn from the set 3, 5, 7, 9, and the even numbers were drawn from the set 2, 4, 6, 8, displayed on screen in yellow sans-serif with font size 22. The consonant letters were drawn from the set G, K, M, R and vowel letters from the set A, E, I, U, also displayed on screen in yellow sans-serif with font size 22. To help participants to keep track of the task sequence, the letter/number pair was presented on a 2*2 yellow grid (5 cm each side), moving around clockwise inside the grid. Participants were told to respond to the letter only when the letter/number pair was shown in one of the top two cells, and to respond to the number only when the pair was shown in one of the bottom two cells. In the number task, participants were asked to press the left button if the number was odd and the right button if the number was even. In the letter task, participants were asked to press the left button if the letter was a vowel and the right button if the letter was a consonant. The inter-trial interval was 150 ms.

Intelligence test. Raven’s advanced progressive matrices (Raven, Raven & Court, 1998) were used to measure non-verbal reasoning ability. The Raven advance test is the most

difficult of the Raven's Matrices tests, and was designed to differentiate among people with "superior intellectual ability" (Raven et al., 1998). This paper-and-pencil test has 48 items, consisting of 2 sets, with 12 diagrammatic puzzles in Set I (for practice) and 36 puzzles in Set II (for data analysis, with a full score of 36). Each item in the test contains a figure with a missing piece, and participants are required to select one out of eight possible answers to fit the missing space from the pattern.

4.1.3. Procedure

Participants in the control group completed all three paradigms. Best performers completed only the shape/filling paradigm and the letter/number paradigm. Since the color/shape task was the same as the Condition 650-500 in Experiment 1B, we re-used the data of the best performers from this condition only. As before, participants had up to 1,500 ms to make a response after target onset. If no or an incorrect response was given within 1,500 ms, error feedback appeared on screen for 1 second. In each paradigm, participants completed a 50-trial block of each single task to practice the task-rules, followed by a 200-trial mixed block with both tasks intermixed. Note that the tasks were randomly mixed in the mixed block of the color/shape and the shape/filling paradigms but not in the number/letter paradigm. After completing the task-switching paradigms, all participants took part in a one-hour Raven's intelligence test.

4.2. Results

Data preprocessing was the same as in Experiment 1B. After exclusion of trials, the number of valid trials ranged between 486 and 583 for the nine best-performing participants and between 376 and 519 for the nine participants in the control group. Next, we conducted conventional ANOVAs on mean RTs and ERs. In addition, we applied GLMMs to confirm group effects and to capture individual differences in RTs.

4.2.1. Task-switching analyses

Mean RTs and ERs are summarized in Appendix A. Two four-way ANOVAs with mixed effects were conducted on the mean RTs and ERs of each participant. Group (best-performing, control) served as between-subjects factor whereas Trial transition (task-repeat, task-switch), Congruency (congruent, incongruent) and Paradigm (colour/shape, shape/filling, and letter/number) were within-subjects factors.

For mean RTs, we observed a significant main effect of Group, $F(1, 16) = 9.12, p = .008, \eta^2_p = .36$. Best-performing participants (605 ms) had significantly faster responses compared to the participants in the control group (695 ms). There was a significant main effect of Trial transition, $F(1, 16) = 133.89, p < .001, \eta^2_p = .89$. Task-switch trials (707 ms) were slower compared to task-repeat trials (592 ms), indicating a statistically significant RT switch cost of +115 ms. There was a significant main effect of Congruency, $F(1, 16) = 58.32, p < .001, \eta^2_p = .78$. Incongruent trials (662 ms) were slower compared to congruent trials (638 ms), indicating a congruency effect of +24 ms. Participants performed differently across paradigms, $F(2, 32) = 69.71, p < .001, \eta^2_p = .81$. Post-hoc comparisons, corrected after Holm (Holm, 1979), revealed that participants were significantly faster in the color/shape paradigm (509 ms) compared to the letter/number (698 ms) and shape/filling paradigm (742 ms).

Trial transition significantly interacted with Paradigm, $F(2, 32) = 28.14, p < .001, \eta^2_p = .64$. Post-hoc analyses revealed that the switch costs were significant in the letter/number ($SC = \text{switch} - \text{repeat} = +155 \text{ ms}, p < .001$) and shape/filling paradigms ($SC = +149 \text{ ms}, p < .001$), but not in the color/shape paradigm ($SC = +42 \text{ ms}, p = .160$). Trial transition also interacted with Congruency, $F(1, 16) = 5.36, p = .034, \eta^2_p = .25$. Post-hoc analyses revealed that switch costs were smaller in congruent trials ($SC = +107 \text{ ms}, p < .001$) compared to incongruent trials ($SC = +123 \text{ ms}, p < .001$). Importantly, Trial transition significantly interacted with Group, $F(1, 16) = 5.43, p = .033, \eta^2_p = .25$. As shown in Figure 8, best performers ($SC = +92 \text{ ms}, p = .002$) showed smaller switch costs compared to the control

group ($SC = +138$ ms, $p < .001$). We did not find a significant interaction between Group and Paradigm ($F < 1$). Other interaction effects involving Group were not significant.

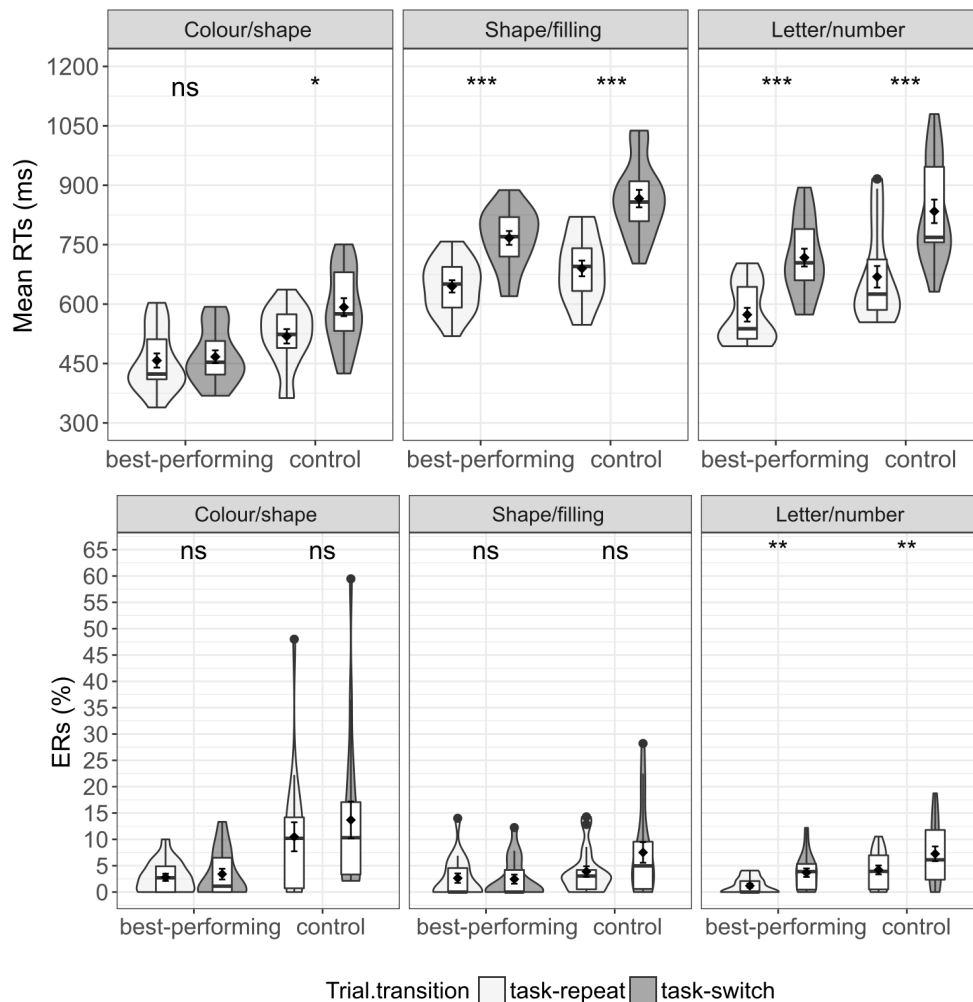


Figure 8. Results of Experiment 1C. Mean RTs (top panels) and ERs (bottom panels) for repeat and switch trials are shown in separate box/violin plots for Group (best-performing, control) and in separate panels for Paradigm (color/shape, shape/filling, letter/number). Black dots represent outliers whereas black diamonds and error bars denote means and standard errors, respectively.

Note. *** $p < .001$; ** $p < .01$; * $p < .05$; ns = non-significant

For error rates, all four main effects were statistically significant. We observed a significant main effect of Group, $F(1, 16) = 9.62, p = .007, \eta^2_p = .38$, as best-performing participants made fewer errors (2.70%) compared to participants in the control group (7.84%). There was a significant main effect of Trial transition, $F(1, 16) = 16.19, p < .001, \eta^2_p = .50$. Participants made more errors in task-switch trials (6.33%) compared to task-repeat trials (4.20%), indicating a significant ER switch cost of +2.13%. There was a significant main effect of Congruency, $F(1, 16) = 35.20, p < .001, \eta^2_p = .69$. Participant made more errors in incongruent trials (8.10%) compared to congruent trials (2.44%), indicating a significant congruency effect of +5.66%. Error rates were also different across paradigms, $F(2, 32) = 9.57, p < .001, \eta^2_p = .37$. Post-hoc analyses indicated that color/shape paradigm (7.60%) had more errors compared to the letter/number paradigm (4.09%) and shape/filling paradigm (4.12%).

Trial transition significantly interacted with Congruency, $F(1, 16) = 18.35, p < .001, \eta^2_p = .53$. Post-hoc analyses showed that the switch costs were larger in incongruent trials (SC = +4.20%, $p = .007$) than in congruent trials (SC = +.07%, $p = .961$). As illustrated in Figure 8, Group significantly interacted with Trial transition, $F(1, 16) = 4.83, p = .043, \eta^2_p = .23$. Post-hoc analyses showed that best performers (SC = +0.97%, $p = .478$) had smaller ER switch costs compared to the control group (SC = +3.29%, $p = .049$). In addition, Group significantly interacted with Paradigm, $F(1, 16) = 6.49, p = .004, \eta^2_p = .29$. Post-hoc analyses revealed that best performers had significantly fewer errors (3.11%) than the control group (12.09%) in the color-shape paradigm ($p < .001$), whereas there was no significant group difference in the letter/number paradigm and shape/filling paradigm. Other interaction effects involving Group did not reach statistical significance.

4.2.2. Individual Differences

In order to study individual differences in RTs, we analyzed the RT measurements from each trial using GLMMs as in Experiments 1A and 1B. We compared the most parsimonious model with Group effects (GLMM 1C.3) with a corresponding model without Group effects (GLMM 1C.2) in order to determine whether factor Group and its interactions improved the model fit. In other words, the model comparison tested whether the distinction between best performers and controls was an important predictor of RTs.

The GLMM 1C.2 turned out to be more parsimonious than 1C.3, suggesting that the distinction between best-performers and controls explained little additional variance in RTs (Appendix B). In GLMM 1C.2, Trial transition, Congruency and Paradigm, and their interactions were treated as fixed effects. The random effects captured individual deviations from the grand mean RT (Intercept), from the main effect of Paradigm and from the interaction between Trial transition and Paradigm. The fixed effects without Group effects mirror the ANOVA results on RTs (Appendix B). On average participants showed significant switch costs (+118 ms, $t = 32.52$, $p < .001$). Switch costs were smaller in the color/shape paradigm (+44 ms) than in the letter/number (+160 ms; $t = -32.68$, $p < .001$) and shape/filling paradigm (+150 ms; $t = -36.17$, $p < .001$).

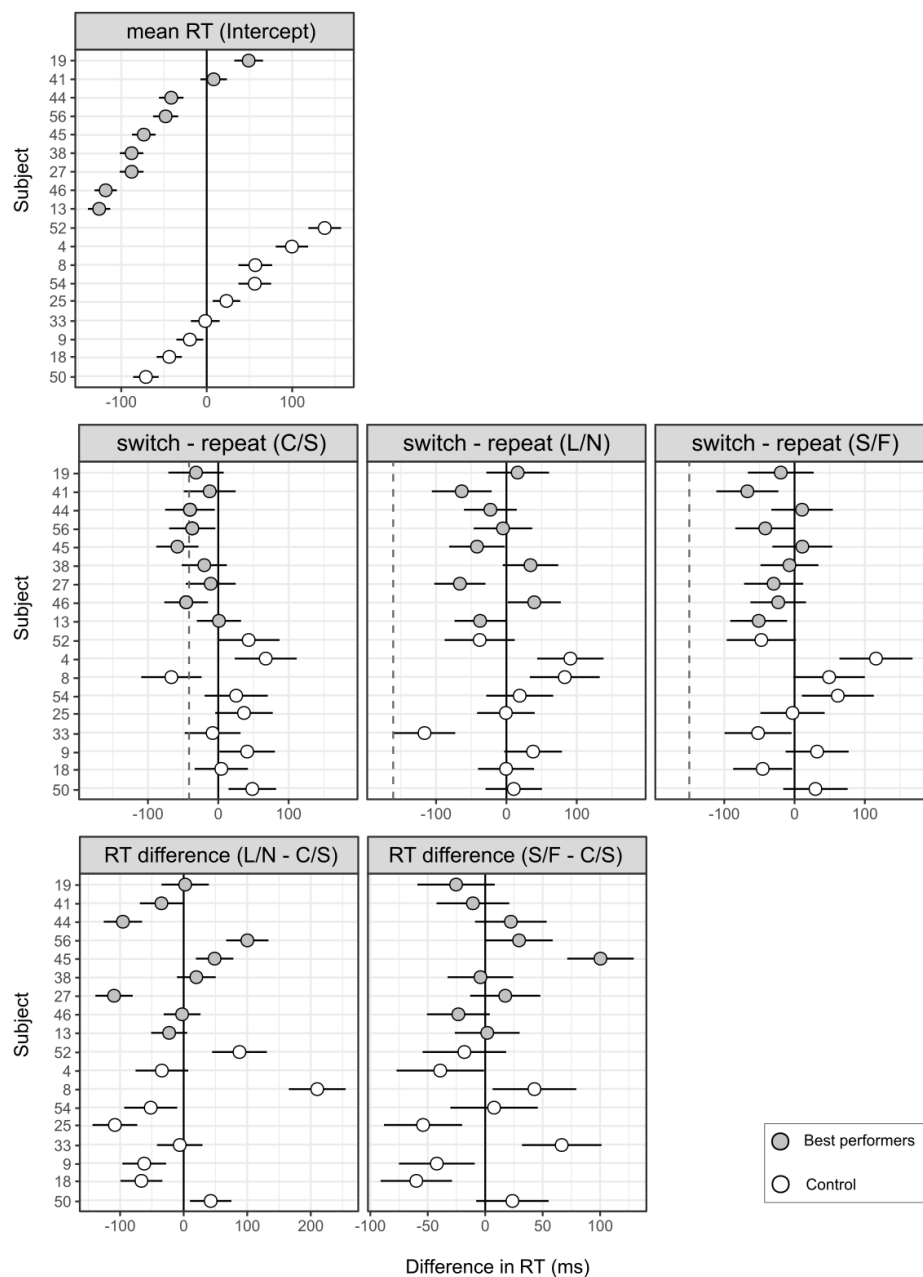


Figure 9. Experiment 1C. Illustration of by-subject random effects for GLMM on RTs.

Subject IDs on the left correspond to participants as in Experiment 1A and 1B. Top panel:

The dotplot shows individual deviations (dots) and 95% confidence intervals (horizontal error bars) from mean RTs (Intercept = grand mean RT of 664 ms, as indicated by the solid vertical line centered on zero). Middle panel: The dotplots from left to right illustrate individual deviations from mean switch costs in the color/shape (+44 ms, as indicated by the solid vertical line centered on zero), letter/number (+160 ms) and shape/filling (+150 ms)

paradigm, respectively. The dashed vertical line in each plot indicates zero switch cost for each paradigm. Bottom panel: The dotplots illustrate individual deviations from the RT difference between color/shape and letter/number paradigm (mean difference = 194 ms, as indicated by the solid vertical line centered on zero), and between color/shape and shape/filling paradigm (mean difference = 230 ms). Please note the different RT scales on the x -axis across plots.

Note. C/S = Color/shape paradigm, L/N = Letter/number paradigm, S/F = Shape/filling paradigm

The by-subject random effects explained considerable RT variance. Figure 9 shows individual differences in mean RTs (top panel), with both groups of participants showing significant deviations from the grand mean RT. Seven of the best performers were significantly faster than average compared to three fast-performing participants in the control group. Comparing Figure 9 with Figure 4 in terms of individual mean RTs (Intercepts) indicates that most participants performed consistently in terms of mean RTs across both experiments. In the control group, for example, Participant 52 was the slowest whereas Participants 18 and 50 were the fastest, ranking similarly in terms of mean RTs in both experiments. In the group of best-performers, Participant 19, who was slower than the sample average RT in Experiment 1A, also responded more slowly in Experiment 1C. In addition, we found that five of the best performers, Participant 27, 38, 45, 46 and 56, responded faster than the sample average in both experiments. Participant 13, however, varied considerably in mean RT. This participant was one of the slowest best performers in Experiment 1A but the fastest participant in Experiment 1C.

Figure 9 also shows that across the three paradigms, some of the participants showed significant deviations from the mean switch costs (middle panel). Importantly, in the color/shape paradigm, all of the best performers except for Participant 13 were close to zero RT switch costs (dashed vertical line), while participants in the control group showed switch costs significantly larger than zero with the exception of Participants 8 and 33. Both groups of participants demonstrated similar switching performance with significant deviations from zero switch costs (dashed vertical lines) in the letter/number and shape/filling paradigm, although best performers exhibited somewhat more homogenous random effects in those paradigms.

Note that best performers and controls deviated significantly from the mean RT difference between paradigms (the bottom panel of Figure 9), suggesting that participants from both groups varied considerably in their RTs between tasks and conditions.

4.2.3. Raven's intelligence scores

The intelligence scores for best performers and controls were compared in a two-sample *t*-test. We found a statistically significant difference between groups, $t(16) = 2.52$, $p = .023$, Cohen's $d = 1.19$. The best performers had on average significantly higher intelligence scores ($Mean = 28.33$, ranging from 17 to 34) compared to the control group ($Mean = 22.33$, ranging from 14 to 29).

4.3. Discussion

In line with our prediction, Experiment 1C confirmed that, even though the zero-error policy was not applied, best performers showed better task-switching performance than participants in the control group. The results of the ANOVAs suggest that best performers had on average shorter RTs and reduced ERs than controls across different paradigms.

Moreover, the analyses suggest that the best-performing participants had on average smaller RT and ER switch costs compared to the controls. The difference in task-switching performance between the two groups may be related to their difference in general intelligence scores, supporting previous studies that have showed a relationship between cognitive abilities and general intelligence (Benedek et al., 2014; Friedman et al., 2006).

Although the comparison between models with and without Group effects suggests that the distinction between best performers and controls was not important, a significant group difference for RT switch costs was detected in the color/shape paradigm: 8 out of 9 best performers had smaller and non-significant switch costs. In contrast, only 2 out of 9 controls showed non-significant switch costs. This confirms our finding from Experiment 1A where the best performers also showed more consistent and more efficient task-switching in this paradigm.

In the shape/filling and the letter/number paradigms, however, the best-performing participants showed significant RT switch costs similar to the control group. In the shape/filling and letter/number paradigm both the cue and the target stimulus were presented simultaneously leaving no or little opportunity to prepare for the upcoming task. As suggested by the *failure-to-engage* and the task-set reconfiguration account, the cue-stimulus interval (CSI) is important because the relevant task-set can be re-configured within a certain CSI (De Jong, 2000; Lindsen & De Jong, 2010; Mayr & Kliegl, 2003; Poboka et al., 2014; Rogers & Monsell, 1995). The critical advantage of the best performers may have been that they were able to efficiently prepare each task-set following a cue, suggesting better cognitive control. This may be related to their higher general intelligence scores. However, consistent with the results in Experiment 1B, their advantage disappeared as soon as the cue-stimulus interval was reduced to zero. We therefore suggest that none of the best-performers qualify as “super-switchers”.

5. General Discussion

In an experiment and two follow-ups we examined individual differences in task switching. In a reasonably large sample of participants, we tried to identify “super-switchers” who were expected to exhibit exceptional task-switching abilities across different conditions and paradigms.

In Experiment 1A we applied a “zero-error policy” to motivate participants to maintain full attention and high engagement during a block of randomly mixed tasks. We found reduced switch costs in their MAX block. In addition, we found large individual differences in participant’s mean RTs and ERs. We identified the 9 best-performing participants in our sample who showed no errors and no significant switch costs. We reasoned that their superior performance may be due to increased motivation to engage in task switching, superior task-switching abilities, or both. In two follow-up experiments, in which participants could make mistakes without the need to restart a block, the best performers were still able to eliminate switch costs in trials with a CSI of 650 ms but not in trials with a CSI of 0 ms. Only in conditions with CSIs, did best performers show better task-switching performance than controls. The results of the two follow-up experiments suggest that the reduced switch costs in best performers is unlikely to be attributed to increased motivation or task engagement because in both follow-up experiments there was less pressure to avoid mistakes.

Alternatively, best performers may have task-switching abilities and/or efficient strategies that can be applied across different task-switching paradigms (cf., Yehene & Meiran, 2007). However, there was no convincing evidence that the best performers had trait-like “super-switcher” abilities. GLMMs revealed that best performers shared RT characteristics with many other participants. In the two follow-ups, we confirmed that best

performers were able to eliminate switch costs when there was a cue-stimulus interval of 650 ms. We attribute this superior performance to more efficient task preparation following a cue.

The reduced switch costs of the best performers supports the *failure-to-engage* account of task-set reconfiguration (De Jong, 2000; Lindsen & De Jong, 2010; Mayr & Kliegl, 2003; Rogers & Monsell, 1995) suggesting that full reconfiguration of the task-set during a CSI of 650 ms is achievable, at least for some participants. In contrast, our findings on best performers seem incompatible with the two-stage theory (Mayr & Kliegl, 2003; Rogers & Monsell, 1995; Rubinstein, Meyer & Evans, 2001). This theory posits that task-rule reconfiguration can only start after onset of a target stimulus which would make it impossible for participants to eliminate switch costs. As a result, each participant should have significant residual switch costs across different conditions.

The identification of best performers addresses the general question, also posed by Haff and Rouder (2017, 2018), whether everyone shows the same “true effect” in cognitive tasks. We found that some individuals showed significant switch costs while a few individuals did not display any switch costs in the pre-cued conditions. In previous studies it was reported that even after extended preparation times ($> 2,000$ ms), significant residual switch costs were found (Meiran et al., 2000, Poboka et al., 2014; Rogers & Monsell, 1995; Schneider, 2016, 2017). Several authors have tried to increase the motivation of participants so that they would prepare for upcoming tasks more efficiently but those studies had limited success in eliminating switch costs (Lien et al., 2005; Meiran & Chorev, 2005; Nieuwenhuis & Monsell, 2002, Schneider, 2016, 2017; see however Verbruggen et al., 2007). These results suggest that, on average, switch costs can be reduced but not eliminated by task preparation so that residual switch costs should always remain. Although this may be true for most individuals, it ignores individual differences in task-switching because participants may be motivated differently, and may have different cognitive abilities and strategies. Striking

evidence of individual differences has been reported in a variety of cognitive tasks (Haff and Rouder, 2017, 2018; Medeiros-Ward et al., 2014; Stoet & Snyder, 2003, 2007; Watson & Strayer, 2010, 2012).

We studied individual differences in task switching. We first conducted ANOVAs on averaged RTs and ERs and found significant mean switch costs, confirming the results of previous task-switching experiments. In addition, we employed general linear mixed models (GLMMs) on single-trial RTs in order to study how individuals varied in their performance across conditions, paradigms, and experiments. We identified best performers, who seemed more capable in task-switching, and showed minimal switch costs in some experimental conditions. Nevertheless, their superior performance did not generalize to conditions and paradigms with simultaneous presentation of cue and target stimulus. Here they showed individual differences and significant switch costs similar to a control group. We argue that analysing averaged performances may overlook individual variability across conditions and paradigms, and may be responsible for the commonly observed residual switch costs in previous task-switching studies (e.g., De Jong, 2000; Merian et al., 2000; Altmann, 2004; Schneider, 2016, 2017). It is possible that although significant residual switch costs were reported, a good number of participants may have successfully eliminated switch costs in various conditions.

Further studies are needed to identify what gave the best performers an advantage in task switching over controls. The Raven's intelligence test suggests that best performers had slightly higher general intelligence, which may be related to improved executive functioning and cognitive abilities. More specifically, best performers may have developed more efficient cue encoding, rule activation, or both. Compared to a paradigm with "two-to-one cue-task mappings", task switching with simpler "one-to-one cue-task mappings" should simplify perceptual processing of multiple cues. With simpler one-to-one cue-task mappings best

performers might quickly translate a task cue (i.e., a solid triangle) into a “task-name mediator” (e.g., “color” in trials with triangle pointing upward), followed by earlier task-goal and task-rule retrieval. This is consistent with the idea of *mediated retrieval* (Logan & Bundesen, 2004; Logan & Schneider, 2006). It is also possible that best performers employed other more specific switching strategies: Based on the *cue-task association hypothesis* proposed by Arbuthnott & Woodward (2002), the best performers may have established stronger associations between task cues and task representations after extensive practice of the color/shape tasks. As soon as a cue is presented, the relevant task feature and category-response mappings are immediately activated in working memory, so that responses in task-switch trials are as fast and accurate as responses in task-repeat trials. As mentioned before, another explanation may be that participants with no or reduced switch costs did not “fail to engage” (De Jong, 2000; Lindsen & De Jong, 2010; Mayr & Kliegl, 2003; Rogers & Monsell, 1995). In contrast, participants with switch costs “failed to engage” in task-set reconfiguration, effectively performing task switching according to the two-stage theory (Mayr & Kliegl, 2003; Rogers & Monsell, 1995; Rubinstein, Meyer & Evans, 2001). These possibilities may be addressed in future research.

The difference in general intelligence between best performers and controls has to be interpreted with caution. Previous studies indicated a strong relationship between information updating and general intelligence (Benedek et al., 2014; Friedman et al., 2006), suggesting that higher intelligence scores may be related to improved goal-updating capabilities, resulting in fewer errors and lower switch costs in task switching. However, there are multiple sub-processes involved in preparation that may collectively lead to improved task-switching performance. Thus, it remains unclear whether the group differences in general intelligence can fully explain group differences in task-switching performance.

6. Conclusion

In the present paper, we investigated individual differences in task-switching. By focusing on individual response times and error rates, we identified best-performing participants who showed superior switching performance in conditions with cue-stimulus intervals. However, in two follow-up experiments the best-performing participants exhibited no superior task-switching in conditions and paradigms with simultaneous presentation of cue and target, performing similar to a group of control participants. The advantage of the best performers may be related to faster than average processing of cue information and rapid task-set reconfiguration before target onset. This advantage suggests better cognitive control which may be related to their higher general intelligence scores. Although we were unable to identify “super-switchers” in our sample, we suggest that a more detailed study of individual switching performances may help to reveal individual differences in switching strategies and executive control.

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Appendix A Supplementary results

Supplementary Figures and Tables in Experiment 1A, 1B and 1C

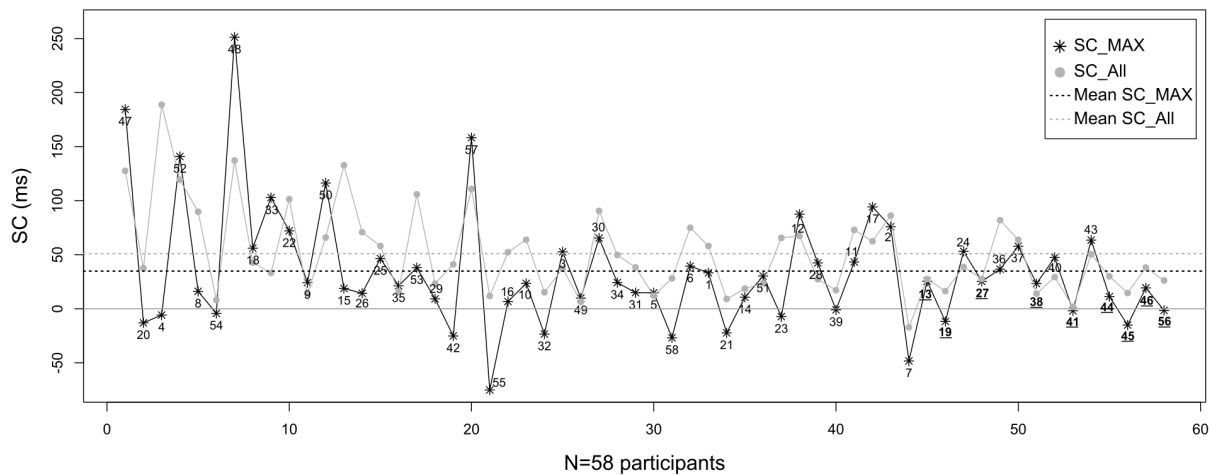
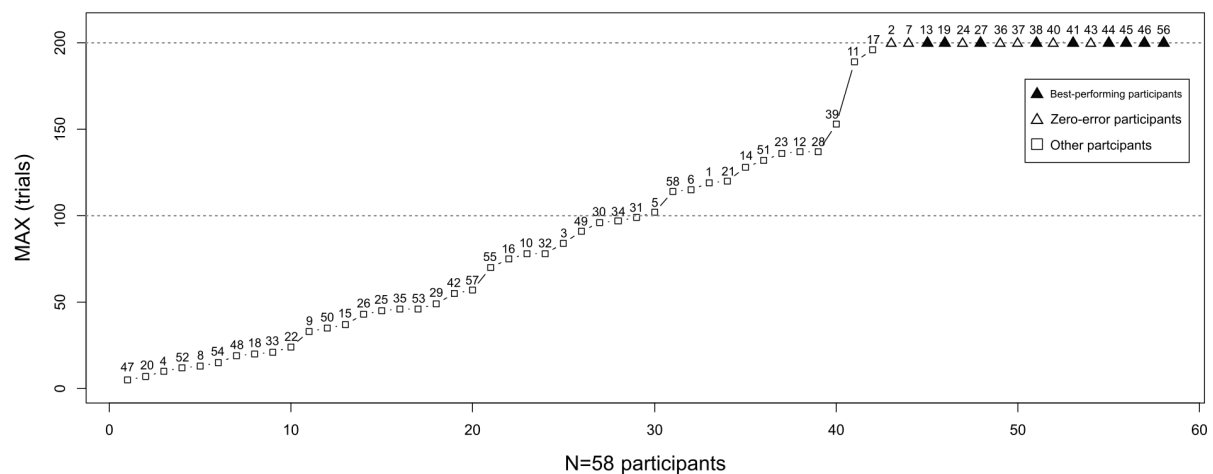
A.**B.**

Figure A1. Experiment 1A. Individual variation in task switching. **A.** Individual switch cost (SC from MAX blocks, and from all mixed blocks, in *ms*). **B.** MAX trials (maximum number of consecutive trials correct). Triangles and corresponding numbers reflect participants who did not make any mistakes in MAX trials. Among them, solid triangles and the corresponding numbers in the two plots denote the 9 best-performing participants.

Note: Please note that the zero-error performers who labeled with open triangles showed significant switch costs. Participant 7 had zero mistakes and showed significantly negative switch costs (switch - repeat = -47 ms, $p = .011$). Therefore, Participants 7 was not

considered as a typical best-performer (be accurate and fast in task-switch trials similar as in task-repeat trials). Other participants (labeled with open squares) made frequent errors in their MAX block.

Table A1

Experiment 1B. Mean RTs (in ms) and error rates (ER as %) of 9 super-switchers.

ITI	Trial transition	CSI = 0 ms		CSI = 650 ms	
		<i>RT</i>	<i>ER</i>	<i>RT</i>	<i>ER</i>
150 ms	Repeat	700 (8.45)	4.57 (1.81)	457 (5.83)	1.08 (1.19)
	Switch	786 (6.38)	3.61 (0.98)	462 (5.41)	2.81 (2.97)
500 ms	Repeat	715 (7.57)	4.14 (1.07)	457 (6.58)	2.81 (2.59)
	Switch	804 (6.37)	4.83 (1.43)	469 (6.04)	3.32 (2.94)

Note. Standard errors are presented in parentheses

Table A2

Experiment 1C. Mean RTs (in ms) and error rates (ER as %)

Paradigms	Trial transition and Congruency	Best-performing ($N = 9$)		Control ($N = 9$)	
		<i>RT</i>	<i>ER</i>	<i>RT</i>	<i>ER</i>
Colour/ shape	RepCon	446 (22.71)	2.31 (.86)	508 (28.04)	5.04 (2.11)
	RepInc	470 (28.53)	3.29 (1.10)	529 (24.13)	15.94 (4.52)
	SwiCon	456 (23.86)	1.14 (.60)	574 (36.02)	5.10 (1.35)
	SwiInc	478 (22.66)	5.67 (1.67)	611 (28.27)	22.26 (5.67)
Shape/ filling	RepCon	629 (21.75)	1.02 (.72)	679 (32.42)	2.13 (.79)
	RepInc	661 (21.88)	4.25 (1.50)	701 (24.29)	5.65 (1.68)
	SwiCon	738 (26.77)	.22 (.22)	854 (32.98)	1.91 (.85)
	SwiInc	796 (19.13)	4.68 (1.37)	879 (30.53)	13.12 (2.79)
Letter/ number	RepCon	579 (27.27)	.97 (.51)	633 (39.94)	2.96 (1.35)
	RepInc	567 (22.92)	1.43 (.52)	675 (39.19)	5.44 (.90)
	SwiCon	701 (30.49)	2.38 (.71)	827 (48.16)	4.06 (1.49)
	SwiInc	734 (33.86)	4.97 (1.35)	842 (37.49)	10.47 (1.87)

Note. Standard errors are presented in parentheses

RepCon = Repeat Congruent; RepInc = Repeat Incongruent; SwiCon = Switch Congruent;
SwiInc = Switch Incongruent

Appendix B. Supplementary results

GLMMs in Experiment 1A, Experiment 1B, Experiment 1C

In each experiment, we modelled the skewed RT data by a Gamma distribution (family = Gamma and link = “identity”) using the lme4 package in R (Bates, Mächler, Bolker, & Walker, 2015). We conducted GLMM comparisons between the simplest (the first model in each table) and the most complex model (the last model in each table) that converged, in order to identify the most parsimonious fixed and random-effect model. According to the information criteria AIC (Akaike information criterion; Akaike, 1973) as well as BIC (Bayesian information criterion; Schwarz, 1978), the best model of each experiment is presented in bold.

The formula of each converged model is stated in the syntax of the lme4 package in R. As shown in the following tables, the factors outside the parentheses denote fixed effects and their interactions. The term inside the parentheses denotes the random intercept for each participant or subject (Bates et al., 2015). The random intercept “1” captures individual deviations from the group-average in RTs. The other random effects describe individual deviations from the corresponding fixed effect.

We have reported the full results of random effects in the main text. Because of the unbalanced data and conditions in Experiment 1 A, we have included the full results of fixed effects in the main text. As the results of the fixed effects of GLMM models in Experiment 1B and Experiment 1C are very similar to those of the analyses of variance (ANOVA), we have only highlighted important results of the fixed effects from GLMMs in the main body of the article. GLMM model comparisons as well as the full description of fixed effects of the best fitted models are reported here.

Experiment 1A GLMMs

We modelled the skewed RT data from the MAX blocks. Models listed in Table B1 range from a simple GLMM 1A.1 with main fixed effects and random intercept to a complex GLMM 1A.3 with full factorial fixed effects and specific random effects. GLMM 1A.2 was the most parsimonious model giving the lowest AIC and BIC values. The factors “Task”, “Trial transition” and “Congruency” outside the parentheses denote fixed effects and their interactions. The random intercept “1” inside the parentheses captures individual deviations from the group-average in RTs. The other random effects “Task” and “Trial transition” inside the parentheses describe individual deviations from the corresponding fixed effect of Task and Trial transition. For Experiment 1A, both the random effects and fixed effects were reported in the main text.

Table B1

Experiment 1A GLMM comparisons based on 58 participants’ RT data in the MAX block (the best model is in bold; GLMM 1A.2).

<i>Model</i>	<i>Models (family = Gamma (link = “identity”))</i>	<i>Df</i>	<i>AIC</i>	<i>BIC</i>	<i>LogLik</i>	<i>dev</i>	<i>Chisq</i>	<i>Pr (>Chisq)</i>
GLMM 1A.1	RT ~ Task + Trial.transition + Congruency + (1 subject)	6	79191	79231	-39589	79179		
GLMM 1A.2	RT ~ Task * Trial.transition * Congruency + (1+Task+Trial.transition subject)	15	79115	79216	-39543	79085	93.77	< .001 ***
GLMM 1A.3	RT ~ Task * Trial.transition * Cuetype * CSI + (1+Task*Congruency subject)	26	79174	79349	-39561	791226	0.00	1.00

Experiment 1B GLMMs

Table B2

Experiment 1B GLMM comparisons based on RT data in the identified best-performing participants (the best model is in bold; GLMM 1B.3).

<i>Model</i>	<i>Models (family = Gamma (link = "identity"))</i>	<i>Df</i>	<i>AIC</i>	<i>BIC</i>	<i>LogLik</i>	<i>dev</i>	<i>Chisq</i>	<i>Pr (>Chisq)</i>
GLMM 1B.1	RT ~ Trial.transition+CSI+ITI + (1 subject)	6	75652	75692	-37820	75640		
GLMM 1B.2	RT ~ Trial.transition*CSI*ITI + (1 subject)	10	75576	75643	-37778	75556	83.32	< .001 ***
GLMM 1B.3	RT ~ Trial.transition*CSI* ITI+ (1+CSI+ITI+ Trial.transition:CSI subject)	24	75374	75534	-37663	75326	230.33	< .001 ***

Models listed in Table B2 range from a simple GLMM 1B.1 with main fixed effects and random intercept to a complex GLMM 1B.3 with full factorial fixed effects and specific random effects. GLMM 1B.3 was the most parsimonious model giving the lowest AIC and BIC values. The factor “Trial transition”, “CSI” and “ITI” outside the parentheses denote fixed effects and their interactions. The terms inside the parentheses denote the random intercept, the main effect CSI and ITI and the interaction between CSI and Trial transition for each participant or subject.

The fixed effect of GLMM 1B.3 supports the ANOVA results on RT that responses were significantly faster in CSI 650 ms (470 ms) compared to CSI 0 (762 ms), $t = -92.58$, $p < .001$. Responses were slower in task-switch trials (637 ms) compared to task-repeat trials (596 ms), $t = 12.75$, $p < .001$. Trial transition significantly interacted with CSI, $t = -20.80$, $p < .001$, suggesting that switch costs were smaller in CSI 650 ms (+4 ms) than in CSI 0 (+79 ms). Switch costs were not different between ITIs, $t = 0.92$, $p = .360$. No other effects reached significance.

Experiment 1C GLMMs

Table B3

Experiment 1C GLMM comparisons on RT data (the best model is in bold; GLMM 1C.2).

<i>Model names</i>	<i>Models (family = Gamma (link = "identity"))</i>	<i>Df</i>	<i>AIC</i>	<i>BIC</i>	<i>LogLik</i>	<i>dev</i>	<i>Chisq</i>	<i>Pr (>Chisq)</i>
GLMM 1C.1	RT ~ Congruency +Trial.transition + Paradigm + Group + (1 subject)	8	114873	114930	-57428	114857		
GLMM 1C.2	RT ~ Congruency* Trial.transition* Paradigm + (1+Paradigm: Trial.transition+Paradigm subject)	34	113985	114225	-56958	113917	26	< .001 ***
GLMM 1C.3	RT ~ Congruency* Trial.transition* Paradigm*Group + (1+Paradigm: Trial.transition+Paradigm subject)	46	113991	114317	-56950	113899	12	.13

Note. The model formula is stated in the syntax of the lme4 package in R.

Models listed in Table B3 range from a simple GLMM 1C.1 with main fixed effects and random intercept to a complex GLMM 1C.3 with full factorial fixed effects and specific random effects. GLMM 1C.2 was the most parsimonious model giving the lowest AIC and BIC values. The factor “Trial transition”, “Congruency” and “Paradigm” outside the parentheses denote fixed effects and their interactions. The terms inside the parentheses denote the random intercept, the effect of Paradigm and the interaction between Trial transition and Paradigm for each participant or subject.

The fixed effect of GLMM 1C.2 supports the ANOVA results in Experiment 1B that response times were shorter in task-repeat trials (604 ms) than in task-switch trials (723 ms), indicating a significant switch cost of +119 ms, $t = 32.52$, $p < .001$. Response times were shorter in congruent trials (651 ms) than incongruent trials (676 ms), indicating a significant

congruency effect of +25 ms, $t = 10.28$, $p < .001$. Responses were more quickly in the color/shape paradigm (522 ms), than in the letter/number paradigm (716 ms; $t = 65.59$, $p < .001$) and shape/filling paradigm (752 ms; $t = 72.41$, $p < .001$).

In addition, the model reveals significant two-way interactions. Switch costs were smaller in congruent trials (+109 ms) than in incongruent trials (+127 ms), $t = -6.50$, $p < .001$. Switch costs were smaller in the color/shape paradigm (+44 ms) than in the letter/number (+160 ms; $t = -32.68$, $p < .001$) and shape/filling paradigm (+150 ms; $t = -36.17$, $p < .001$). Congruency effect in the color/shape paradigm (+25 ms) was slightly larger than in the letter/number paradigm (+13 ms, $t = 3.32$, $p < .001$), but slightly smaller than in the shape/filling paradigm (+38 ms, $t = -4.81$, $p < .001$). No other effects were statistically significant.